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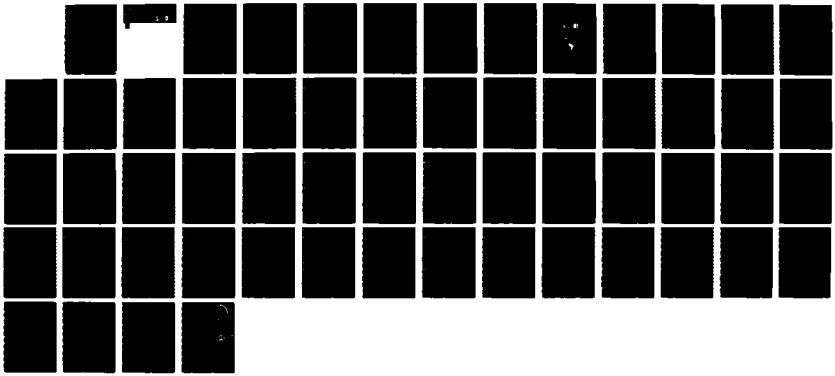

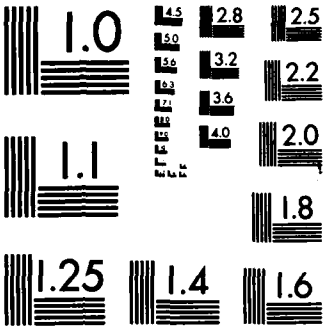

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ANALOGICAL INFERENCE AND ANALOGICAL ACCESS

by

Dedre Gentner

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Analogy is a powerful technique in commonsense learning and reasoning. People use analogies in problem solving, in developing mental models of a new domain, and in communicating knowledge. To model these natural uses of analogy, we need to understand the whole process of analogizing from the first, starting with access and ending with drawing inferences or extracting a principle from an analogy.

In this paper, I first review the structure-mapping theory of analogical processing and describe a simulation of the theory. I then extend this framework to accessing analogy. I discuss some recent research in our lab that suggests that the accessibility of an analogical match is governed by different factors from its inferential soundness. Finally, I consider some competing theoretical approaches to analogy and suggest an integrated architecture for analogical processing.

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Analogical Inference

and Analogical Access

Dedre Gentner

University of Illinois

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Address correspondence to:

Dedre Gentner
University of Illinois
Department of Psychology
603 East Daniel Street
Champaign, Illinois 61820

Abstract

Analogy is a powerful technique in commonsense learning and reasoning. People use analogies in problem solving, in developing mental models of a new domain, and in gaining and communicating knowledge. To model natural uses of analogy, we need to understand the whole process of drawing an analogy, beginning with accessing a potential analog and ending with drawing inferences or extracting a principle from the analogy.

In this paper, I first review the structure-mapping theory of analogical mapping and inference and describe a simulation of the theory. I then extend this framework to the issue of how potential analogs are accessed. I discuss recent research that suggests that the *accessibility* of an analogical match is governed by different factors from its *inferential soundness*. Finally, I consider some competing theoretical approaches and suggest an integrated architecture for analogical processing.

My goal in this research is to understand how analogy and similarity work in experiential learning and reasoning. To understand analogical learning, we need to know how analogy is accessed and how it is used. In my previous research I focused on how analogy is used in making inferences. More recently I have been investigating access to analogies in long term memory. In this paper I will put these lines together into a cognitive architecture for analogy.

The theoretical framework for this paper is the structure-mapping theory of analogy, which gives the rules for analogical mapping and also functions as a core theory for a broader treatment of analogical learning (Gentner, 1980, 1982, 1983; Gentner & Gentner, 1983). The central intuition is that an analogy is a mapping of knowledge from one domain (the base) into another (the target) which conveys that a system of relations that holds among the base objects also holds among the target objects. In analogy, the target objects do not have to resemble their corresponding base objects. Objects are placed in correspondence by virtue of their like roles in the common relational structure. Thus an analogy is a way of noticing relational commonalties independently of the objects in which those relations are embedded. Central to analogy is the principle of *systematicity*: people prefer to map systems of predicates, rather than isolated predicates. Analogy conveys a system of connected knowledge, not a mere assortment of independent facts. Preferring systems of predicates that contain higher-order relations with inferential import is a structural expression of this tacit preference for coherence and deductive power in analogy.

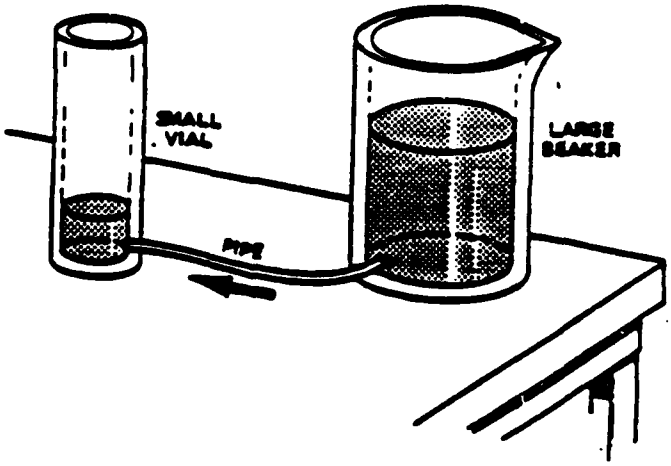
I first describe the basic theory and then discuss the Structure-mapping Engine, a simulation written by Brian Falkenhainer and Ken Forbus

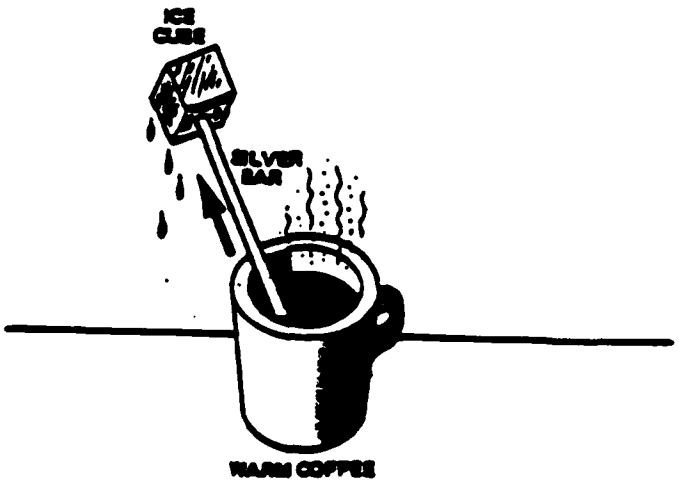
(Falkenhainer, Forbus & Gentner, 1986). In interpreting an analogy, people seek to put the objects of the base in correspondence with the objects in the target so as to obtain maximum structural match. That is, they seek the mapping that maximizes consistency and systematicity. Consistency means that the mapping is 1-1: each object in the base is assigned at most one object in the target. Systematicity refers to the mapping of connected systems of relations, rather than isolated predicates. I will also use the term *systematicity* at times to refer to the presence of a system of relations in a given domain. The systematicity principle states that a base predicate that belongs to a mappable system of mutually interconnecting relations is more likely to be imported into the target than is an isolated predicate. A <u>system</u> of relations refers to an interconnected predicate structure in which higher-order predicates enforce constraints among lower-order predicates. A <u>mappable</u> system in the base is one that can be mapped into the target system without contradiction, and ideally with some partial matching with existing target predicates. The more matches are found between the predicates of the base system and existing predicates in the target, the more support there is for mapping other members of the base system. Thus, in an analogical mapping we are looking for a system of relations that can apply in both base and target. In determining the correspondence between objects in the base and objects in the target, the object descriptions themselves can be arbitrarily different; corresponding objects don't have to resemble each other at all. Instead, the object correspondences are chosen to achieve a consistent and maximally systematic match between predicates in the base and those in the target.

To illustrate the structure-mapping rules, we turn to a specific example: the analogy between heat-flow and water-flow. Figure 1 shows a water-flow situation and an analogous heat-flow situation (adapted from Buckley, 1979, pp

Figure 1

Examples of Physical Situations Involving
Water-flow and Heat-flow





15-25). Figure 2 shows the representation a learner might have of the two situations.

This network[1] represents a portion of what a person might know about the water and heat situations illustrated in the previous figure. These representations are the ones given to the Structure-mapping Engine, as described below. Note that we assume the learner begins with a richer representation of the water situation than of the heat situation.[2]

In order to comprehend the analogy "Heat is like water." a learner must find the set of object correspondences that allows systematic matching between the two domains. In so doing, the learner must:

- disregard object attributes, such as CYLINDRICAL(beaker)
- *map base relations into the target domain*
- observe systematicity: i.e., find a system of relations that can apply in both domains. here, the pressure-difference structure in the water domain

CAUSE(GREATER-THAN[PRESSURE(beaker), PRESSURE(vial)],

[FLOW(water, pipe, beaker, vial)])

which maps into the temperature-difference structure in the heat domain

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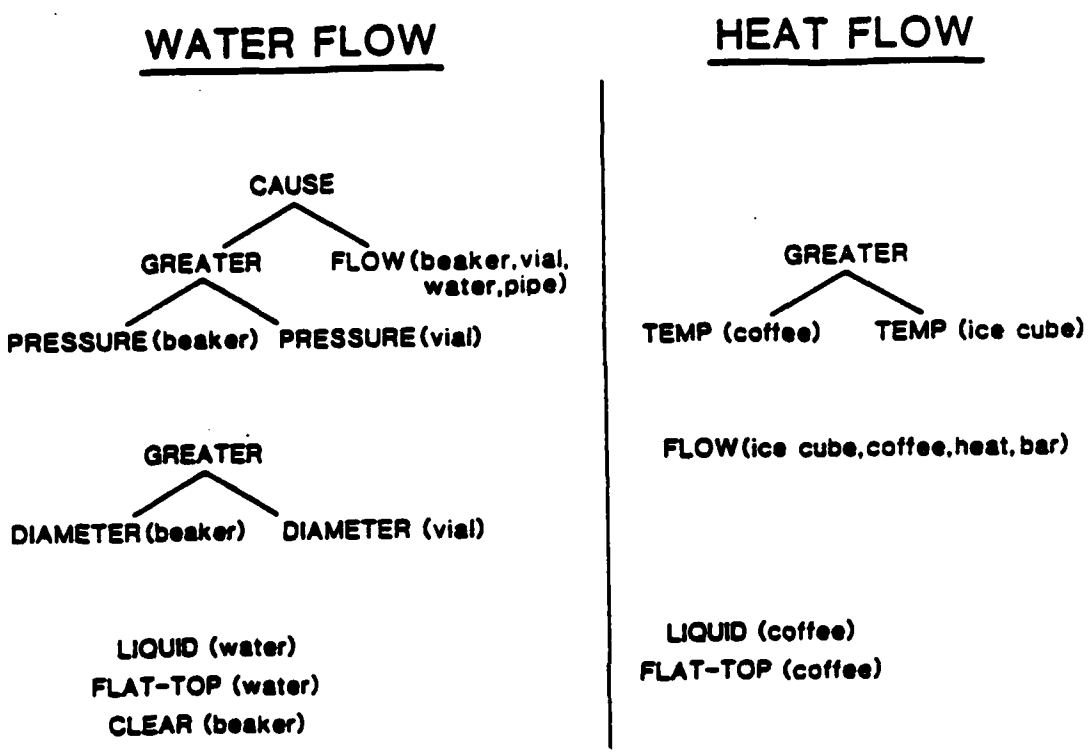
1. In this and other figures, predicates, including both relations and functions, are written in upper case and objects are written in lower case. A more detailed representation of the heat/water analogy is given in Forbus & Gentner (1983, 1986).

2. This analogy has been important in the history of theories of heat. It probably underlies the caloric theory of heat, and it was used by Carnot (1824) to illustrate the interrelation between heat and temperature. (See Gentner & Jeziorski (in preparation) for a discussion of this history.)

Figure 2

Representations of Water and Heat



CAUSE(GREATER-THAN[TEMPERATURE(coffee), TEMPERATURE(ice)],

[FLOW(heat, bar, coffee, ice)]).

- discard isolated relations, such as

GREATER-THAN[DIAMETER(beaker), DIAMETER(vial)]

The object correspondences between the two domains that allow for the best match turn out to be

water --> heat; pipe --> metal bar;

beaker -->coffee; vial --> ice.

As noted earlier, the object correspondences -- water/heat, beaker/coffee, vial/ice, and pipe/bar -- and the function correspondence **PRESSURE/TEMPERATURE**[3] are determined not by any intrinsic similarity between the objects, but by their role in the systematic relational structure. Systematicity also determines which relations get carried across. The reason that

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3. In this analogy, the function **PRESSURE** in the water domain must be matched with **TEMPERATURE** in the heat domain. Like objects and their attributes, functions on objects in the base can be put in correspondence with different functions in the target in order to permit mapping a larger systematic structure. This is a change from my former position, which only distinguished between object-attributes (one-place predicates), which were allowed to match nonidentically, and relations (2-or-more-place predicates), which had to match identically. I now distinguish functions on objects (including n-place functions) as a separate class, which can match nonidentically. The rationale is that such functions are basically aspects of object descriptions. Like objects and their attributes, they can be put into correspondence with different functions in the target. In other words, the essential distinction is between objects and their descriptions on the one hand and relational structure on the other. My initial formulation in terms of one-place and n-place predicates was too stringent. I thank Ken Forbus, Brian Falkenhainer and Janice Skorstad for discussions on this issue.

GREATER-THAN[PRESSURE(beaker), PRESSURE(vial)]

is preserved is that it is part of a system of higher-order constraining relations -- in this case, the system governed by the higher-order relation CAUSE -- that partially matches a relational system in the target. In contrast, the relation

GREATER-THAN[DIAMETER(beaker), DIAMETER(vial)]

does not belong to a common systematic structure shared by the base and target domains, and so is discarded in the interpretation.

However, it is important to note that which predicates survive in the interpretation depends on the match between the two domains. With a different target domain, the DIAMETER difference will be part of the analogy. For example, suppose that we keep the same base domain -- the water system shown in Figure 2 -- but change the target domain to two objects differing not only in their *temperature* but also in their *specific heat*: say, a metal ball-bearing and a marble. Assuming equal mass, they will also have different *heat capacities*. With this new target, the natural interpretation concerns capacity differences[4] in the base, as well as level or pressure differences. Now each system involves two interrelated variables: (1) the initial variable of LEVEL (TEMPERATURE) which tells us in which direction water (heat) will flow to achieve equilibrium and (2) a second variable of CAPACITY which determines which vessel will experience the greatest change in LEVEL in achieving

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4. For continuity I have used DIAMETER as the predicate, although CROSS-SECTIONAL AREA would be more accurate. Also, note that there might have been a similar heat-capacity difference between the coffee and ice cube in the original heat figure; but without specifying the masses, this difference could not be assumed.

equilibrium. Now the most systematic relational system that can be mapped to the target is

CAUSE (GREATER-THAN [DIAMETER (beaker), DIAMETER (vial)],

GREATER-THAN [CHANGE-OF-PRESSURE(vial),CHANGE-OF-PRESSURE(beaker)])

This carries over into the target as

CAUSE (GREATER-THAN [HEAT-CAP.(marble), HEAT-CAP.(ball)],

GREATER-THAN [CHANGE-OF-TEMP.(ball), CHANGE-OF-TEMP.(marble)]).

Because the target shares a larger relational system with the base, the natural interpretation of the analogy is now more complex. This illustrates that, for a given base domain, the mapping for a particular target is determined by the best match -- i.e., the most systematic and consistent relational match -- between base and target.[5] The only case in which the base domain by itself determines the interpretation is that in which nothing is initially known about the target; then matching does not apply and the mapping is one of pure carryover from base to target. In the more normal case when information is known about both base and target, the interpretation is based on both matching between base and target and carryover of predicates from base to target (Gentner, in press).

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5. I stress this point because it apparently can be misunderstood; Holyoak (1985) writes that the interpretation of an analogy in structure-mapping depends only on an analysis of the structure of the base domain. To forestall such misconceptions I stress that (as with other kinds of similarity comparisons) the interpretation of an analogy in structure-mapping involves a *match* -- in this case the most systematic consistent match -- between two domains.

There are a few further points to notice here. First, the order of operations is probably variable. I suspect that often the learner begins with relational matching and mapping and uses the relational matches to determine the object correspondences. (This is the way the simulation performs, as described below.) However, sometimes the object-correspondences are the first step: for example, in cases when the learner is explicitly told the object correspondences. Second, note that the systematicity principle requires a *mappable* relational system. If the predicates of the base system generate contradictions in the target, then another system must be selected. Third, a member of a base relational system that can successfully be mapped into the target provides support for other members of that system.

Finally, it is useful to distinguish two extremes of analogical processing:

- (1) <u>pure matching</u>: all the predicates of the base system are matched with predicates in the target system. In this case the analogy serves not to communicate new knowledge but to focus attention on a particular common system of predicates.

- (2) <u>pure mapping</u>: the learner is given the object correspondences and simply carries across a system of predicates from the base to the target. This is a case of maximal new knowledge.

These extremes are rare; most analogies involve both matching and mapping. Typically there is a partial match between base and target systems, which then sanctions the mapping of further predicates from the base to the target.

<u>The Structure-Mapping Engine</u>. The Structure-Mapping Engine (SME) is a simulation of the structure-mapping process written by Brian Falkenhainer and Ken Forbus. I describe it briefly here (For a more complete description, see Falkenhainer, Forbus, & Gentner, 1986). Given representations of the base and

target, SME uses systematicity and structural consistency to determine the best mapping(s). When SME is run in its basic analogy mode, only relational structure counts in the match. But SME can also be run with different match rules to simulate mere-appearance matches (only object descriptions count) and literal similarity matches (both object descriptions and relational structure counts in the match). Because literal similarity matches show a broad range of SME's behavior, I will describe the match rules that simulate literal similarity.

SME is given as input structured representations of the water and heat situations, as shown in Figure 2.[6] The order of events is as follows:

(1) *Local matches.* SME starts by finding potential matches between single items in the base and target. For each entity and predicate in the base, it finds the set of entities or predicates in the target that could plausibly match that item. These potential correspondences (*match hypotheses*) are determined by a set of simple rules: for example,

- (1) if two relations have the same name, create a match hypothesis;

- (2) for every match hypothesis between relations, check their corresponding arguments: if both are entities, or if both are functions, then create a match hypothesis between them.

For example, given the representations in Figure 2, rule (1) creates match hypotheses between the GREATER THAN relations that occur in base and target. Then rule (2) creates match hypotheses between their arguments, since both are

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6. Note that the representations contain extraneous matches such as LIQUID(water) and LIQUID(coffee). These spurious matches are included to simulate a learner's uncertainty about what matters and to give SME the possibility of making errors.

functions. Note that at this stage the system is entertaining two different -- and inconsistent -- match hypotheses involving GREATER THAN: one in which PRESSURE is matched with TEMPERATURE, and one in which DIAMETER is matched with TEMPERATURE. Thus, at this stage the program will have a large number of local matches.

Another set of rules assigns *evidence scores* to these local matches: e.g.,

- (1) Increase the evidence for a match if the base and target predicate have the same name.

- (2) Increase the evidence for a given match if there is evidence for a match among the parent relations -- i.e., the immediately governing higher-order relations.

Rule (1) reflects a preference for relational identity and rule (2) reflects a preference for systematicity. It is at this stage that the GREATER-THAN--PRESSURE system in the water domain begins to gain an advantage over the GREATER-THAN--DIAMETER system. This is because the PRESSURE system has more layers of parent predicates that match with the heat system, which leads to higher local evidence scores for PRESSURE than for DIAMETER.

(2) *Constructing global matches.* The next stage is to collect systems of matches that use consistent (i.e., 1-1) entity-pairings. SME first propagates entity-correspondences up each relational chain to create systems of match hypotheses that use the same entity-pairings. It then combines these into the largest possible systems of predicates with consistent object-mappings. These global matches (called Gmaps) are the possible interpretations of the analogy. Associated with each Gmap is a (possibly empty) set of *candidate inferences* --

predicates that are part of the base system but were not initially present in the corresponding target system.

(3) *Evaluating global matches.* The global matches are then given a structural evaluation, which depends chiefly on the local match evidence.[7]

An important aspect of SME is that the global matches (Maps) sanction *candidate inferences*: predicates from the base that get mapped into the target domain. These are base predicates that were not originally present in the target, but which can be imported into the target by virtue of belonging to a system that is largely shared by base and target. For example, in the heat/water scenario shown here, the water representation contains the full pressure-difference system, while the heat representation lacks the higher-order CAUSE predicate. That is, it contains only the two first-order predicates

GREATER-THAN[TEMPERATURE(coffee), TEMPERATURE(ice)]

and

[[FLOW(heat, bar, coffee, ice)])

In this case, the system brings across the higher-order predicate CAUSE from the base domain. In essence, it postulates that there may be more structure in the target than it initially knew about.

SME's interpretation is based on selecting the most systematic consistent mappable structure. Thus computing systematicity precedes and determines the final selection of object correspondences. Indeed, even in literal similarity

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7. SME also has the capability to consider the number of candidate inferences supported and the graph-theoretic structure in assigning the evaluation, but the ramifications of these options have not yet been explored.

mode, as illustrated here, achieving a maximally consistent relational match can outweigh placing similar objects in correspondence.[8]

SME's matching process is entirely structural. The internal processes of the analogy engine are not directly influenced by the system's problem-solving goals (although, as discussed below, the reasoner's plans and goals can have *indirect* influence since they influence the inputs to the analogy engine). But by promoting deep relational systems, the systematicity principle operates to promote predicates that participate in causal systems and in other constraint relations. Yet this purely structural mechanism guarantees that the set of candidate mappings will be as interesting -- in the sense that a mutually interconnected system of predicates is interesting -- as the knowledge base allows.

Kinds of Similarity. I have claimed that in interpreting analogical matches, only relational predicates count. There is evidence that in judging the aptness of a metaphoric comparison, people do indeed favor such relational mappings (Gentner, 1980, 1986; Gentner & Block, 1983; Gentner & Landers, 1985). But to give a complete psychological account of learning by analogy and similarity, we must also consider other kinds of similarity matches. As was discussed above, not only analogy but also other kinds of similarity can be characterized by the distribution of relational and attributional predicates that are mapped. In *analogy*, only relational predicates are mapped. In *literal similarity*, both relational predicates and object-attributes are mapped. In *mere-appearance* matches, it is chiefly object descriptions that are mapped.

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8. This view of literal similarity is a departure from the 'feature-list' view that has been dominant in cognitive psychology (e.g., Tversky, 1977). In ongoing research, Doug Medin, Robert Goldstone and I have found evidence for effects on relational structure on similarity judgements, even with simple geometric figures.

Table 1 shows examples of these different kinds of similarity comparison. The central assumption here is that it is not merely the relative *number* of shared versus nonshared predicates that matters -- although that is certainly important, as Tversky (1977) has shown -- but also the *kinds* of predicates that match. For a longer discussion of similarity types see Gentner, 1986).

Table 1

Kinds of Domain Comparison

	ATT	REL	EXAMPLE
Literal Similarity	Many	Many	Milk is like water.
Analogy	Few	Many	Heat is like water.
Abstraction	Few	Many	Heat flow is a through-variable.
Anomaly	Few	Few	Coffee is like the solar system.
Mere Appearance	Many	Few	The glass tabletop gleamed like a pool of water.

To illustrate these distinctions, consider this series of related examples.

(1) *Analogy*. As discussed above, the analogy "Heat is like water." conveys a relational system:

CAUSE(GREATER-THAN[PRESSURE(beaker), PRESSURE(vial)],

[FLOW(water, pipe, beaker, vial)])

is mapped into

CAUSE(GREATER-THAN[TEMPERATURE(coffee), TEMPERATURE(ice)],

[FLOW(heat, bar, coffee, ice)]).

(2) *Literal similarity*. The comparison "Kool-Aid is like water." conveys that most of the water description can be applied to Kool-Aid. In literal similarity, both object descriptions, including attributes like

FLAT-TOP(water) and CYLINDRICAL(beaker)

and relational predicates, such as the systematic structure discussed above, are mapped over.

(3) *Relational abstraction*. The abstract statement "Heat is a through-variable," which might be available to a student who knows some system dynamics, conveys that heat can be thought of as a flow variable that moves across a potential difference. This potential difference requires an across-variable: in this case, temperature. This abstraction, when applied to the heat domain, conveys much the same relational structure as is conveyed by the heat/water analogy (1). The difference is that in the abstract base domain of through-variables and across-variables, there are no concrete properties of objects to be left behind in the mapping.

(4) *Mere-appearance match.* A mere-appearance statement, such as "The table top looked like water," is one with overlap in lower-order predicates -- object-descriptions and some first-order spatial relations -- but not in higher-order relations. Here, the color and texture of the water is mapped onto the table. Although mere-appearance matches are limited in their explanatory utility, they are important in a psychological account of learning, for two reasons: (1) they often occur among novice learners; and (2) in general, mere-appearance matches may be highly accessible in long-term memory.

These contrasts are not dichotomies but continua, . For example, for both analogy and literal similarity, the base and target share relational structure. If that is *all* they share, then the comparison is an analogy. To the extent that the domains also share common object descriptions, the comparison becomes literal similarity. Another continuum exists between analogy and relational abstraction. In both cases, the base and target share relational structure and do not share object descriptions. Here the continuum is in the nature of the base representation. If the base representation includes concrete objects whose individual attributes must be left behind in the mapping, the comparison is an analogy. As the object nodes of the base domain become more abstract and variable-like, making the comparison becomes more like invoking an abstraction.

Accessing versus Soundness

With these distinctions, we are ready to ask what governs spontaneous access to analogy and similarity. Are the similarities that promote access the same as those that enter into mapping and judging the worth of analogies? To clarify the discussion, let us decompose analogical reasoning into access and

mapping-plus-inference. [For a more detailed treatment of the subprocesses in analogy, see Clement (1981, 1983) and Gentner (1987, in press).] *Access* is the process of matching a base situation in memory with a given target situation a person is faced with. In other words, it is the process whereby a current target situation reminds a person of a base situation in his memory. *Mapping* occurs after a base situation has been accessed from memory. In mapping, the predicates of the base are matched with corresponding predicates of the target according to the rules given above, including consistency and systematicity. In cases where a highly systematic relational structure can indeed be mapped into the target domain, structure-mapping predicts that people will consider the analogy *sound*. Such an analogy can support inferences: because the base and target share systematic relational structure, any additional predicates from the base system can be carried into the target system as candidate inferences. Thus structure-mapping predicts that shared systematicity should be a major determinant of how sound people believe an analogy to be.

Gentner & Landers (1985) investigated the accessibility and subjective soundness of different kinds of similarity matches. The experiment had a two-fold purpose: (1) it tested the prediction that systematicity determines the subjective soundness of a match; and (2) it compared the accessibility of analogy with that of other kinds of similarity matches. This study was designed to create a situation resembling naturalistic long-term memory access. The subjects were 30 students from the MIT Psychology Department. We first gave the subjects a large number (32) of stories to read and remember. One week later, we brought them back, showed them a new set of stories and asked them to tell us if they were reminded of any of the original stories. Finally, they rated the story pairs for their inferential soundness, as explained below. The stories were carefully designed to embody different kinds

of similarity matches. There were three kinds of similarity matches between base and target: mere appearance matches, true analogies and false analogies, as follows:

- *mere appearance (MA)*: first-order relations and object-attributes match
- *true analogy (TA)*: first-order relations and higher-order relations match
- *false analogy (FA)*: only the first-order relations match.

Note that in all three cases, the base and target shared first-order relations. The three similarity conditions differed in which, if any, other commonalities also existed. Table 2 shows an example set of four scenarios: a base scenario plus one example of each of the three kinds of matches.

In the first session, all subjects read the same 18 base stories and 14 filler stories. They were told to read carefully and remember the stories. In the second session, six to eight days later, subjects received a workbook of 18 new target stories: 6 MA targets, 6 TA targets, and 6 FA targets. That is, each target was similar -- in one of the three ways described above -- to one of the 18 base stories the subject had read. The target stories were read in random order. Subjects were divided into 3 groups to counterbalance which type of match occurred in which stories. For each target story read, subjects were instructed to write down any base story they were reminded of, as completely as possible.

The soundness task was given to subjects after they had completed the matching task. In this task, subjects were given workbook showing 18 pairs of stories and asked to rate each pair for the "soundness" of the match between the two stories (explained as "when two situations match well enough to make a strong

TABLE 2

Sample Story Set for the Access and Soundness Experiment

(Gentner & Landers, 1985)

BASE story

Karla, an old hawk, lived at the top of a tall oak tree. One afternoon, she saw a hunter on the ground with a bow with some crude arrows that had no feathers. The hunter took aim and shot at the hawk but missed. Karla knew the hunter wanted her feathers so she glided down to the hunter and offered to give him a few. The hunter was so greatful that he pledged never to shoot at the hawk again. He went off and shot deer instead.

True Analogy TARGET

Once there was a small country called Zerdia that learned to make the world's smartest computer.

One day Zerdia was attacked by its warlike neighbor, Gagrach. But the missiles were badly aimed and the attack failed. The Zerdian government realized that Gagrach wanted Zeridian computers so it offered to sell some of its computers to the country. The government of Gagrach was very pleased. It promised never to attack Zerdia again.

Mere Appearance TARGET

Once there was an eagle named Zerdia who donated a few of her tailfeathers to a sportsman so he would promise never to attack eagles.

One day Zerdia was nesting high on a rocky cliff when she saw the sportsman coming with a crossbow. Zerdia flew down to meet the man, but he attacked and felled her with a single bolt. As she fluttered to the ground Zerdia realized that the bolt had her own tailfeathers on it.

False Analogy TARGET

Once there was a small country called Zerdia that learned to make the world's smartest computer. Zerdia sold one of its supercomputers to its neighbor, Gagrach, so Gagrach would promise never to attack Zerdia.

But one day Zerdia was overwhelmed by a surprise attack from Gagrach. As it capitulated the crippled government of Zerdia realized that the attacker's missiles had been guided by Zerdian supercomputers.

argument from one to the other"). The first story in each pair was one of the base stories from the first session, and the second story was the matching target story the subject had received (whether or not he or she had noticed the match). Thus, each subject rated 1/3 MA, 1/3 TA, and 1/3 FA matches. Subjects used a 1-5 scale, where 5 = highly sound and 1 = spurious.

To score the reminding task, two judges read each of the workbooks and scored the accuracy of the recalled base stories. The judges did not know which experimental condition subjects were in, nor what kind of match they had been given. They used a scale ranging from 5 (excellent recall) to 1 (poor recall), with 0 being used when subjects made no reminding response at all or recalled a *different* story. [9] In addition to this overall score, we also computed a *flat score*. For this score, we counted all recalls with an overall score of 2 or better. This simply measured whether any genuine recall had occurred, without worrying about whether the recall was of high quality.

Results of the Soundness Task. Figure 3a shows the results of the soundness-rating task. As predicted by structure-mapping theory, subjects judged the true analogies, the only pairs that shared higher-order structure, to be far more sound than the other two kinds of pairs. The MA and FA pairs, which did not share systematic structure, were judged to be unsound.[10] The difference between false analogies and true analogies is particularly interesting for structure-mapping theory, for these two match types differed *only* in the presence of higher-order relational structure. The fact that true analogies

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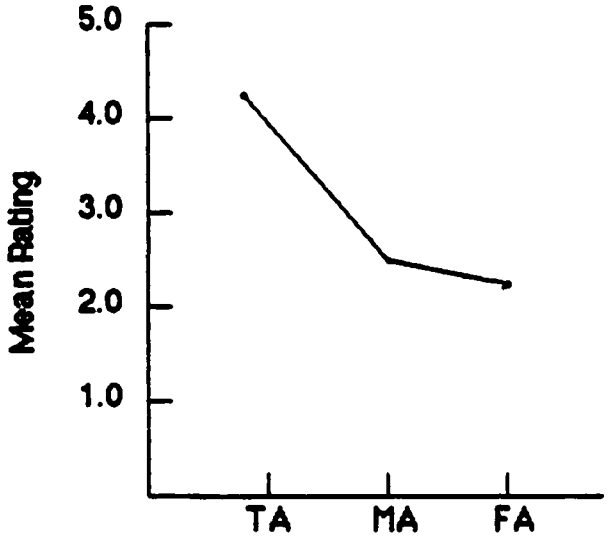
9. There was good agreement among the judges: they were within one point of each other 97% of the time.

10. These patterns were confirmed by an analysis of variance and by planned-comparison t-tests. The differences between TA and MA and between TA and FA are significant ($p<.001$ in each case), and the difference between MA and FA is not significant ($p=.802$).

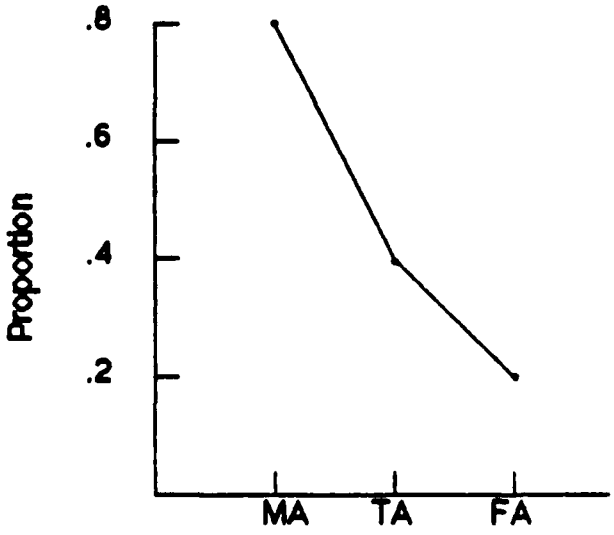
Figure 3

Results Of The Access Experiment
(Gentner And Landers, 1985)

a. Mean Rating of Soundness of Match



b. Proportion of Base Stories Recalled Given
Different Kinds of Matches



were rated as significantly more sound than false analogies is evidence that it is not just shared *relations* but shared *higher-order relations* that determine analogical soundness. These results help confirm the importance of systematicity in human analogical reasoning.

Results of the Reminding Task. The results of the reminding task are quite different. As Figure 3b shows, mere appearance matches are by far the best remembered. This is true for both scoring methods -- overall recall score and flat-match score.[11]

These results suggest that different kinds of similarity matches are weighted differently in determining the accessibility and the inferential soundness of an analogy. In the reminding task, mere appearance matches were by far the best accessed. True analogies accessed only half as often and false analogies about one third as often. Evidently, access to memory is heavily influenced by surface similarity between the base and target. In contrast, in judging soundness it is systematic structural overlap that counts. Thus, although mere-appearance matches were highly successful at leading subjects to access the base, such matches were nonetheless judged by the same subjects to be spurious comparisons. The matches that people find easiest to make are not the ones they find most valuable in inference.

We have recently replicated these results, adding a literal similarity condition, and the results show the same pattern (Gentner & Rattermann, in preparation). It appears that the subprocesses involved in analogical <u>access</u>

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11. Both overall analyses of variance and planned-comparison t-tests indicate that all of the differences --- MA-TA, MA-FA, and TA-FA --- are significant for both overall and flat matching scores ($p<.001$ in all six tests).

and judging analogical soundness may be influenced to different degrees by different kinds of similarity.[12]

- Accessibility is promoted by overall similarity, but perhaps especially by surface similarity.

- Inferential power is governed by similarity of higher-order structures.

These access results accord with other research on access (Gick & Holyoak, 1980, 1983; Reed, 1987; Reed, Ernst & Banerji, 1974; Ross, 1984, 1986; Ross & Sofka, 1986). In this research it has reliably been demonstrated that subjects in a problem-solving task often fail to access prior material that is analogous to their current problem. For example, in Gick and Holyoak's (1980, 1983) studies, subjects were told to solve a problem shortly after hearing a story that was in fact analogous to the problem. A substantial number of subjects failed to access the potential analogy -- and therefore could not solve the problem -- yet, when told that the prior material was relevant, they could solve the problem immediately. This means that their stored information about the prior story formed a good analogy to their current problem; but the analogical commonalities were not sufficient to cause them to spontaneously access this material. Further, the work of Ross (1984, 1986; Ross & Sofka, 1986), Reed (1987) and Novick (1985) indicates that surface commonalties are important in promoting access to prior material. Thus, surface similarity appears to be a major factor in accessing material in long-term memory.

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12. Strictly speaking, we cannot compare the importance of surface and structural similarity in a given process, just as we cannot compare the importance of form and color. What we can say is that the relative contribution of surface to structural similarity is greater in access than in inference. I thank Brian Ross for discussion of this point.

These results are problematic for the view that memory is normally indexed by top-level structures such as plans and goals. (Carbonell, 1983; Hammond, 1984). For if access were based on shared plans and goals, the true analogy targets should have been the best cues for the base stories. But this was not the case. Evidently, access to memory is heavily influenced by surface similarity between the base and target, and not merely by similarity in causal structure or in plans and goals. Contrary to the plausible intuition of importance-governed indexing, *analogical access* has a different sensitivity profile from *analogical inference*.

It could be argued that the Gentner & Landers and Gick & Holyoak results are not representative of normal access patterns. As Hammond (personal communication, January, 1986) points out, it may be that a story-reading task is not representative of real-life encoding tasks, in which plans and goals determine how things are indexed (e.g., Burstein, 1983; Carbonell, 1983; Schank, 1982). By this argument, the emphasis on surface information in access in these studies results from the fact that the subjects were not in a goal-driven state at the time of original story encoding. This is a point worth further investigation. There is research suggesting that the amount of relational access depends in part on the nature of the original encoding (Schumacher, 1987). Thus it seems plausible that if the original situation had been more goal-driven, the effects of surface commonalities might have been lower. However, this does not appear to be the whole answer, for there is heavy reliance on surface information in access even in problem-solving contexts, in which the learner should be goal-driven throughout. Subjects who are solving problems both at the time of the original base problem and at the time of the original target problem still show a sizable surface bias in

access (Novick, 1985; Reed, 1987; Reed, Dempster & Ettinger, 1985; Reed, Ernst, & Banerji, 1974; Ross, 1984, 1985, in press).

Clearly, these results cannot be taken to mean that analogical access -- including plan-based access -- never occurs. Such remindings occur at occasionally in commonsense reasoning (e.g., Leake & Owens, 1986; Kass, 1986; Schank, 1982) as well as in expert problem-solving (Clement, 1981, 1983, 1986) and, historically, in scientific discovery (Gentner, 1982; Gentner & Jeziorski, in preparation). Indeed, in the Gentner & Landers study true analogies led to remindings about 40% of the time. A correct model of analogy will have to account both for the fact that analogical reminding is relatively unlikely and for the fact that it does sometimes occur. Further research should clarify the conditions under which analogical access occurs.

From a machine-learning standpoint, it may seem that humans are very badly designed. The human bias for overall-similarity matches rather than analogical remindings must deprive us of countless potential insights. But there may be good reason for this bias. Human data bases are typically very large, orders of magnitude larger than those of any current A.I. systems. An access bias for literal similarity serves to reduce the number of spontaneous matches that have to be checked. If we noticed all the analogical remindings that are inherent in our data bases, the costs of checking potential matches might be prohibitive.

But although this explanation might justify our conservative preference for overall similarity, it does not explain why our access mechanisms also produce mere-appearance matches. At first glance, this seems really dumb. My speculation is that, for beings with good perceptual systems, access on the basis of object descriptions may be a reasonable heuristic for obtaining

literal similarity matches. Surface information is cheap -- that is we seem to process it very easily -- and, at least in concrete physical domains, it is fairly reliable. By and large, what looks like a tiger *is* a tiger. Thus the cost/reliability tradeoff for humans in use of surface information may be rather reasonable. Whether we should design machines with the same access biases is not clear. If relative costs are different in machine learning systems then a different tradeoff might be preferable. The harder it is to give a machine learning system rich perceptual representations and the easier it is to design efficient methods for checking large numbers of potential similarity matches, the less the payoff for using a human-like access system.

Aside from efficiency of access, it is possible that a bias for literal similarity has subtle but deep advantages in learning very complex systems -- such as language, or the laws of the physical world -- where the appropriate relational structures cannot be predicted in advance. Forbus & Gentner (1983, 1986) have suggested that in such domains initial learning is best described as massive storage of exemplars. Then through similarity matches -- initially literal similarity matches and later analogies -- common relational structure gradually becomes more salient. (It's assumed here that making a similarity match heightens the salience of the matching features in subsequent memory (e.g., Gick & Holyoak, 1983).) Although such a system is initially slow, its advantage is that its eventual abstractions are based on regularities in domain structure rather than on the learner's initial preconceptions.

Related Research:
Pragmatic versus Structural Accounts

Some aspects of structure-mapping have received convergent support in artificial intelligence and psychology. There is widespread agreement on the basic elements of one-to-one mappings of objects with carryover of predicates (Burstein, 1983; Carbonell, 1983; Darden, 1980; Greiner, 1986; Hobbs, 1979; Hofstadter, 1984; Indurkhya, 1985; Kedar-Cabelli, 1985) Reed, 1987; Reed, Dempster & Ettinger, 1985; Rumelhart & Norman, 1981; Van Lehn & Brown, 1980; and Winston, 1980, 1982). However, accounts vary in the nature of the selection principle that determines just *which* predicates come over in analogy. In structure-mapping, the selection rules are structural: namely, a *preference* for systematic relational matches. Pragmatic and contextual factors influence the matching process only indirectly, by influencing the input to the matcher and by providing pragmatic criteria against which results of the match are judged. (See Figure 4 below.) Although many researchers use systematicity as part of their selection criteria, it is often augmented by specific content knowledge or pragmatic information. For example, an important early system was Winston's (1980, 1982) system, which used a selection criterion based on common object properties and classes but also on specific relational content: it looked for *causal* relations in its importance-guided matching algorithm. Other recent accounts have taken a more strongly pragmatic view, emphasizing the central role of plans and goals in the analogical mapping process. For example, Carbonell (1981, 1983) proposed that people comprehend analogies according to an *invariance hierarchy* -- an ordered sequence of ten interpretation types, starting with shared *goal-expectations* and continuing through *planning strategies*, then *causal structures* and on down to *object identities* as the last resort. This account focuses on plans and

goals as the most important higher-order relations for analogical mapping. It suggests that a reasoner will always begin by seeking a common goal, then try for a common plan, then a common causal structure, and so on. This is a very different kind of process from the one suggested here, in that the interpretation types are tried in a fixed preset order, rather than (as here) derived by matching structures. As a process model, the invariance hierarchy seems rather implausible. This is especially true for science analogies. In the heat flow/water flow analogy, for example, it seems unlikely that people first try to find a goal-expectation common to heat and water, then try for a common planning strategy, and only then turn to common causal structure. However, Carbonell's hierarchy is a useful start on a taxonomy of the kinds of relational structures that analogies can highlight.

The purest exposition of the pragmatic view is that of Holyoak (1985). He proposes an entirely pragmatic account in which structural principles play no role. In Holyoak's account, there are no independent structural distinctions among predicate types; the *only* distinction between surface and structural commonalties is that of relevance to the current plan. As Holyoak (1985, p. 81) states:

> It is possible, based on the taxonomy of mapping relations discussed earlier, to draw a distinction between *surface* and *structural* similarities and dissimilarities. An identity between two problem situations that plays no causal role in determining the possible solutions to one or the other analog constitutes a surface similarity. Similarly, a structure-preserving difference, as defined earlier, constitutes a surface dissimilarity. In contrast, identities that influence goal attainment constitute structural similarities, and structure-violating differences constitute structural dissimilarities. Note that the distinction between surface and structural similarities, as used here, hinges on the relevance of the property in question to attainment of a successful solution. The distinction thus crucially depends on the goal of the problem solver.

Notice that this account is solely pragmatic. Relevance does not *augment* considerations of predicate structure, but *replaces* them. Holyoak argues that systematicity is an epiphenomenon: what passes for structural matching is actually the reasoner's attention to the causal assertions that support current goals. *Structural* similarities are defined as "identities that influence goal attainment." and *surface* similarity as "an identity between two problem situations that plays no causal role in determining the possible solutions to one or the other analog." Thus the distinction between surface and structural similarities "hinges on the relevance of the property in question to attainment of a successful solution. The distinction thus crucially depends on the goal of the problem solver."

This view has an immediate appeal: it focuses attention on analogy as an aspect of goal-directed reasoning. Like the work of Burstein (1983), Carbonell (1981) and Kedar-Cabelli (1985), it emphasizes the importance of contextual relevance in analogical processing. These are aspects of analogy that must be taken into consideration; and indeed I will suggest a way to model these factors below (See Figure 4.). However, Holyoak's account goes much further than the others mentioned: it promises to *replace* structural considerations like systematicity with an ecologically natural notion of the reasoner's goal. But looked at closely, the pragmatic proposal reveals serious problems.

The first disadvantage of the purely pragmatic account is that, because it is a one-factor system, it cannot capture the distinction between soundness and relevance. An analogy can be rejected in a problem-solving situation for two different reasons: it can be judged unsound -- i.e., lacking in sufficient structural overlap to support importing inferences from base to target -- or it can be judged irrelevant -- i.e., as supporting inferences in the target but not the inferences needed at the moment. To capture both these

possibilities, a two-factor theory is necessary: pragmatic criteria, which govern relevance, must be separated from structural criteria, which govern soundness. The purely relevance-based account encounters other serious problems as well: since 'structural identities' (a bit of a misnomer here) are defined as *goal-relevant identities*, the interpretation mechanism requires that the reasoner have a goal in order to derive an interpretation of an analogy. Outside of a goal-context, there is no basis for choosing which matches to keep. Yet we know that people can comprehend an analogy in isolation.

Finally, it's not clear whether a purely pragmatic account is computationally feasible. Holyoak and Thagard (1986) outline a computer simulation of analogical processing called PI. However, there does not appear to be any published account to date containing enough detail to ascertain whether it operates according to the pragmatic account, whether it runs on more than the single example described, and how sufficient or efficient it is. I will return to these points below, after suggesting what I believe is a better way to model the interaction between structure and context.

Plans and goals in a structural account. Plans, goals and expectations are important throughout cognition (Miller, Gallanter & Pribram, 1960; Schank, 1982; Schank & Abelson, 1977). A complete model of analogical problem solving must take account of the plans and goals of the reasoner (e.g., Burstein, 1983; Holyoak, 1985; Kedar-Cabelli, 1985.)[13] However, the fact that plans and goals are important in analogical reasoning does not mean they should be built into the analogy engine. Analogy occurs in other contexts besides problem-

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13. I thank Mark Burstein for many lively and insightful discussions on this point. His arguments have led me to give plans and goals a more explicit role in my account.

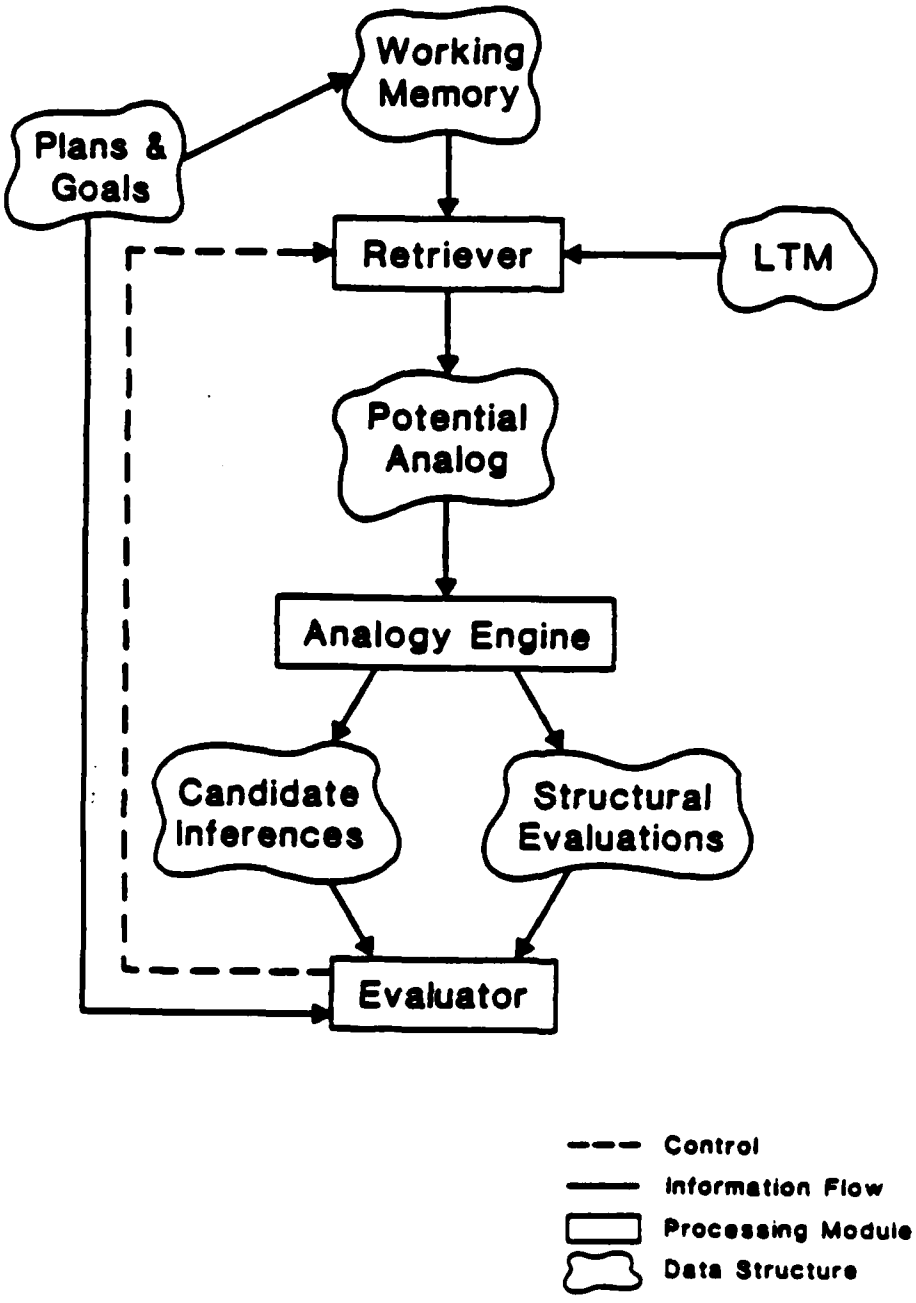
solving. And in the other direction, plans and goals affect many different kinds of human reasoning. In other words, what differentiates analogy from other processes is not the use of plans and goals; it is the nature of the computation performed. What is needed is an account that captures what is specific and essential to analogy, one that is applicable to problem-solving uses of analogy without being restricted to them.

I propose the architecture shown in Figure 4. This architecture provides for a purely structural analogy processor whose input representations and output evaluation are influenced by plans and goals. In a problem-solving situation, the reasoner's goals influence the way the target problem is represented in working memory. This in turn influences what gets accessed. Once the potential base analog is accessed from long-term memory, the analogy engine runs its course. The engine produces an interpretation including candidate inferences and also a structural evaluation. If the structural evaluation is too low -- i.e., if the depth and size of the system of consistently matching predicates is too low -- then the analogy will be rejected on structural grounds. If the analogy passes the structural criterion, then its candidate inferences must be evaluated with respect to the goals of the reasoner. In terms of the computer model, this suggests adding a context-sensitive, expectation-driven module to evaluate the output of SME. Thus, plans and goals influence the process both before and after the analogy engine; but the engine itself is can be run without overt goals. This architecture appears compatible with the combination models proposed by Burstein (1983) and Kedar-Cabelli (1985), which combine structural rules with a pragmatic component so as to choose an interpretation that is both consistent and contextually relevant.

In the model proposed here, both structural properties and contextual-pragmatic considerations enter into analogical problem solving, but they are

Figure 4

A Proposed Cognitive Architecture for Analogical Processing



not equated. Goals are not *required* to define an analogical match. The analogy engine is a well-defined, semi-autonomous system whose results interact with other processes, analogous to the way some natural-language models have postulated semi-autonomous interacting subsystems for syntax, semantics and pragmatics (e.g., Reddy, Erman, Fennell & Neely, 1973). This allows us to capture the fact that analogy must satisfy *both* a structural and a pragmatic criterion. In addition, any candidate inferences that result from an analogy must be tested for validity in the target domain. At a minimum this means checking whether contradictory information already exists; it may also include conducting experiments to verify the predictions (Gentner, 1982; Greiner, 1986). Thus there are three separate evaluation criteria for analogy: soundness, validity and (when appropriate) relevance.

Separating the pragmatic context from the actual analogy processor has other advantages. Unlike purely pragmatic theories, it captures the fact that people can comprehend an analogy in isolation, with no context at all, and that in so doing they appear to use many of the same processes as they do in a problem-solving context. For example, consider this analogy:

Wit is the salt of conversation, not the food. (Hazlitt)

I suspect that most readers can derive its meaning without prior pragmatic context. Furthermore, if someone tried to use this analogy with the goal of demonstrating that being funny is the most important thing in conversation, you would probably feel that the analogy failed to support the speaker's goal. That is, you would be able to derive an independent structurally-based interpretation of the metaphor, which you could then compare with the speaker's goals to see how effectively it supported them. Of course, as with other kinds of processing, analogical mapping should be faster and easier in the context of pragmatic expectations consistent with a correct structural

interpretation, and harder with inconsistent prior pragmatic expectations. But that is very different from saying that plans and goals are required for analogical processing.

I have occasionally heard people defend the goal-centered approach against examples like the above by arguing that in such analogies "the speaker's plans and goals are derived from the match." Of course, but this is exactly my point: without needing any advance knowledge of the speaker's goals, we can apply our analogy engine to derive a common relational structure which we then infer (in the absence of contradictory information) to be the speaker's goal. Thus structural matches are used to determine goals; this is the *opposite* of the claim that goal-relevance must drive the matching.

Another advantage of separating pragmatic relevance from structural matching is that it allows a better account of spontaneous generation of analogy. People often generate analogies that have no obvious relevance to plans and goals. For example, Bowerman (personal communication, June, 1985) reports the following analogical reminding. She heard an ambulance approaching and saw the cars pulling over to the side of the road, one after another. She suddenly thought of a sensitive plant -- a mimosa -- which has the characteristic that when touched its leaves shrink in towards the stem in linear succession along the length of the stem. Examples like this are familiar to all of us. They show that, though analogy may be used to serve our plans and goals, its nature does not *require* a goal-oriented context. The purely pragmatic account of analogy could not handle such examples, since it requires prior plans and goals in order to operate. Holyoak (1985) is aware of this limitation and states that his pragmatic account is meant to apply to analogy in problem-solving. But having to postulate separate processors for analogy in isolation and analogy in problem-solving entails a substantial loss of generality.

One reason for the interest in content-specific or pragmatically driven interpretation processes has been a concern that purely structural information is insufficient to guide analogical mapping. The evidence from the Structure-mapping Engine so far suggests otherwise, since it generates intuitively plausible answers and does so rapidly (Falkenhainer, Forbus & Gentner, 1986). SME is able to reject initially plausible predicate matches like "LIQUID (water) ---> LIQUID (coffee)" purely on the basis of consistency and systematicity. So far SME has performed successfully on over 30 different analogies. Issues of the sufficiency and efficiency this of approach still remain, of course. We are exploring a variety of examples to see where and how the system breaks down. But at present, the structural approach looks quite powerful.

Conclusions

Overall, the advantages of the structure-mapping approach are

(1) Its rules can be stated precisely.

(2) Since the rules are statable in terms of the *structure* of the knowledge representation, we do not have to know in advance which predicates are going to be shared in order to generate or process an analogy.

(3) Separating structural rules from pragmatics allows us to capture the dual requirements of soundness and relevance; and it allows us to capture the commonalities among analogy interpretation across different pragmatic contexts.

(4) The distinctions between object descriptions, relations and higher-order relations lead to a similarity space, with distinct subclasses of similarity based not only on *how many predicates* overlap between base and target, but on *what kind of predicates* overlap.

The results reviewed here have implications for theories of learning by analogy and similarity. First, they indicate that the analogy process is decomposable into different mechanisms, with very different characteristics. Second, they show that an adequate treatment of similarity must distinguish different subclasses of similarity with different psychological privileges. Third, they provide further evidence for the psychological reality of structure-mapping processes in analogy; it appears that people can carry out rather sophisticated structural matches in the course of comprehending analogy. Finally, these results have implications for the nature of similarity itself. Careful analysis of different kinds of predicate matches may be central to modeling the role of analogy and similarity in learning.

Acknowledgments

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Winston, P. H. (1982). Learning new principles from precedents and exercises. *Artificial Intelligence*, *19*, 321-350.

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University of Minnesota
Department of Psychology
Minneapolis, MN 55455

Dr Beth Adelson
Dept of Computer Science
Tufts University
Medford, MA 02155

AFOSR,
Life Sciences Directorate
Bolling Air Force Base
Washington, DC 20332

Dr Robert Ahlers
Code N711
Human Factors Laboratory
Naval Training Systems Center
Orlando, FL 32813

Dr Ed Aiken
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr James Anderson
Brown University
Center for Neural Science
Providence, RI 02912

Dr John R. Anderson
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. Steve Andriole
George Mason University
School of Information
Technology & Engineering
4400 University Drive
Fairfax, VA 22030

Technical Director, ARI
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Gary Aston-Jones
Department of Biology
New York University
1009 Main Bldg
Washington Square
New York, NY 10003

Dr Patricia Baggett
University of Colorado
Department of Psychology
Box 345
Boulder, CO 80309

Dr. Eva L. Baker
UCLA Center for the Study
of Evaluation
145 Moore Hall
University of California
Los Angeles, CA 90024

Dr Meryl S. Baker
Navy Personnel R&D Center
San Diego, CA 92152-6800

prof. dott. Bruno G. Bara
Unita di ricerca di
intelligenza artificiale
Universita di Milano
20122 Milano - via F. Sforza 23
ITALY

Dr. William M. Bart
University of Minnesota
Dept. of Educ. Psychology
330 Burton Hall
178 Pillsbury Dr., S.E.
Minneapolis, MN 55455

Lee Beltracchi
U.S. Nuclear Regulatory Comm.
Washington, D.C. 20555

Dr. Mark H. Bickhard
University of Texas
EDB 504 ED Psych
Austin, Texas 78712

Dr. Gautam Biswas
Department of Computer Science
University of South Carolina
Columbia, SC 29208

Dr. John Black
Teachers College, Columbia Univ.
525 West 121st Street
New York, NY 10027

Dr R. Darrell Bock
University of Chicago
NORC
6030 South Ellis
Chicago, IL 60637

Dr Sue Bogner
Army Research Institute
ATTN PERI-SF
5001 Eisenhower Avenue
Alexandria, VA 22333-5600

Dr Jeff Bonar
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr Gordon H. Bower
Department of Psychology
Stanford University
Stanford, CA 94306

Dr Robert Breaux
Code N-095R
Naval Training Systems Center
Orlando, FL 32813

Dr. Ann Brown
Center for the Study of Reading
University of Illinois
51 Gerty Drive
Champaign, IL 61280

Dr. John S. Brown
XEROX Palo Alto Research
Center
3333 Coyote Road
Palo Alto, CA 94304

Dr. Bruce Buchanan
Computer Science Department
Stanford University
Stanford, CA 94305

Maj. Hugh Burns
AFHRL/IDE
Lowry AFB, CO 80230-5000

Dr Patricia A. Butler
OERI
555 New Jersey Ave., NW
Washington, DC 20208

Distribution List [Illinois/Gentner] NR 667-551

Dr Joseph C Campione
Center for the Study of Reading
University of Illinois
51 Gerty Drive
Champaign, IL 61820

Joanne Capper
Center for Research into Practice
1718 Connecticut Ave., N.W
Washington, DC 20009

Dr Jaime Carbonell
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

Dr Susan Carey
Harvard Graduate School of
Education
337 Gutman Library
Appian Way
Cambridge, MA 02138

Dr Pat Carpenter
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

LCDR Robert Carter
Office of the Chief
of Naval Operations
OP-01B
Pentagon
Washington, DC 20350-2000

Chair, Department of
Psychology
College of Arts and Sciences
Catholic University of
America
Washington, DC 20064

Dr. Fred Chang
Navy Personnel R&D Center
Code 51
San Diego, CA 92152-6800

Dr. Davida Charney
English Department
Penn State University
University Park, PA 16802

Dr Paul R. Chatelier
OUSDRE
Pentagon
Washington, DC 20350-2000

Dr Michelene Chi
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Dr. Susan E. Chipman
1142CS
Personnel and Training Research Program
Office of Naval Research, Code 1142PT
Arlington, VA 22217-5000
(6 copies)

Dr. L. J. Chmura
Computer Science and
Systems Branch
Naval Research Lab.
Washington, DC 20375-5000

Mr Raymond E. Christal
AFHRL/MOE
Brooks AFB, TX 78235

Professor Chu Tien-Chen
Mathematics Department
National Taiwan University
Taipei, TAIWAN

Dr. Yee-Yeen Chu
Perceptronics, Inc.
21111 Erwin Street
Woodland Hills, CA 91367-3713

Dr. William Clancey
Stanford University
Knowledge Systems Laboratory
701 Welch Road, Bldg. C
Palo Alto, CA 94304

Dr. Charles Clifton
Tobin Hall
Department of Psychology
University of
Massachusetts
Amherst, MA 01003

Dr Allan M. Collins
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Stanley Collyer
Office of Naval Technology
Code 222
800 N. Quincy Street
Arlington, VA 22217-5000

Dr. William Crano
Department of Psychology
Texas A&M University
College Station, TX 77843

Brian Dallman
3400 TTW/TTGXS
Lowry AFB, CO 80230-5000

Dr. Laura Davis
NRL/NCARAI, Code 7510
4555 Overlook Ave., SW
Washington, DC 20375-5000

Dr. Natalie Dehn
Department of Computer and
Information Science
University of Oregon
Eugene, OR 97403

Dr. Gerald F DeJong
Artificial Intelligence Group
Coordinated Science Laboratory
University of Illinois
Urbana, IL 61801

Gerry Delacote
Directeur de L'informatique
Scientifique et Technique
CNRS
15, Quai Anatole France
75700 Paris FRANCE

Dr. Sharon Derry
Florida State University
Department of Psychology
Tallahassee, FL 32306

Dr. Andrea di Sessa
University of California
School of Education
Tolman Hall
Berkeley, CA 94720

Distribution List [Illinois/Gentner] NR 667-551

Dr. R. K. Dismukes
Associate Director for Life Sciences
AFOSR
Bolling AFB
Washington, DC 20332

Dr. Stephanie Doan
Code 6021
Naval Air Development Center
Warminster, PA 18974-5000

Dr. Emanuel Donchin
University of Illinois
Department of Psychology
Champaign, IL 61820

Defense Technical
Information Center
Cameron Station, Bldg 5
Alexandria, VA 22314
Attn: TC
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Dr. Thomas M. Duffy
Communications Design Center
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Schenley Park
Pittsburgh, PA 15213

Dr. Richard Duran
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Santa Barbara, CA 93106

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Navy Personnel R&D Center
San Diego, CA 92252

Dr. Susan Embretson
University of Kansas
Psychology Department
426 Fraser
Lawrence, KS 66045

Dr. Randy Engle
Department of Psychology
University of South Carolina
Columbia, SC 29208

Dr. Susan Epstein
Hunter College
144 S. Mountain Avenue
Montclair, NJ 07042

ERIC Facility-Acquisitions
4833 Rugby Avenue
Bethesda, MD 20014

Dr. K. Anders Ericsson
University of Colorado
Department of Psychology
Boulder, CO 80309

Dr. Jean Claude Falmagne
Department of Psychology
New York University
New York, NY 10003

Dr. Beatrice J. Farr
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Pat Federico
Code 511
NPRDC
San Diego, CA 92152-6800

Dr. Paul Feltovich
Southern Illinois University
School of Medicine
Medical Education Department
P.O. Box 3926
Springfield, IL 62708

Mr. Wallace Feurzeig
Educational Technology
Bolt Beranek & Newman
10 Moulton St.
Cambridge, MA 02238

Dr. Gerhard Fischer
University of Colorado
Department of Computer Science
Boulder, CO 80309

J. D. Fletcher
9931 Corsica Street
Vienna VA 22180

Dr. Linda Flower
Carnegie-Mellon University
Department of English
Pittsburgh, PA 15213

Dr. Kenneth D. Forbus
University of Illinois
Department of Computer Science
1304 West Springfield Avenue
Urbana, IL 61801

Dr. Barbara A. Fox
University of Colorado
Department of Linguistics
Boulder, CO 80309

Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

Dr. Norman Frederiksen
Educational Testing Service
Princeton, NJ 08541

Dr. Michael Friendly
Psychology Department
York University
Toronto Ontario
CANADA M3J 1P3

Julie A. Gadsden
Information Technology
Applications Division
Admiralty Research Establishment
Portsdown, Portsmouth PO6 4AA
UNITED KINGDOM

Dr. Michael Genesereth
Stanford University
Computer Science Department
Stanford, CA 94305

Dr. Dedre Gentner
University of Illinois
Department of Psychology
603 E. Daniel St.
Champaign, IL 61820

Chair, Department of
Psychology
George Mason University
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Learning Research
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W. J. Brogden Psychology Bldg.
1202 W. Johnson Street
Madison, WI 53706

Dr. Sam Glucksberg
Department of Psychology
Princeton University
Princeton, NJ 08540

Dr. Susan Goldman
University of California
Santa Barbara, CA 93106

Dr. Sherrie Gott
AFHRL/MODJ
Brooks AFB, TX 78235

Dr. T. Govindaraj
Georgia Institute of Technology
School of Industrial & Systems
Engineering
Atlanta, GA 30332

Dr. Wayne Gray
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. James G. Greeno
University of California
Berkeley, CA 94720

Dr. Dik Gregory
Behavioral Sciences Division
Admiralty Research Establishment
Teddington, Middlesex
ENGLAND

Dr. Gerhard Grossing
Atominstitut
Schuttelstrasse 115
Vienna, AUSTRIA a-1020

Prof. Edward Haertel
School of Education
Stanford University
Stanford, CA 94305

Dr. Henry M. Halff
Halff Resources, Inc.
4918 33rd Road, North
Arlington, VA 22207

Dr. Ronald K. Hambleton
Prof. of Education & Psychology
University of Massachusetts
at Amherst
Hills House
Amherst, MA 01003

Stevan Harnad
Editor, The Behavioral and
Brain Sciences
20 Nassau Street, Suite 240
Princeton, NJ 08540

Dr. Wayne Harvey
SRI International
333 Ravenswood Ave.
Room B-S324
Menlo Park, CA 94025

Dr. Reid Hastie
Northwestern University
Department of Psychology
Evanston, IL 60201

Prof. John R. Hayes
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Barbara Hayes-Roth
Department of Computer Science
Stanford University
Stanford, CA 95305

Dr. Frederick Hayes-Roth
Teknowledge
525 University Ave.
Palo Alto, CA 94301

Dr. Shirley Brice Heath
School of Education
Stanford University
Stanford, CA 94305

Dr. Joan I. Heller
505 Haddon Road
Oakland, CA 94606

Dr. Jim Hollan
Intelligent Systems Group
Institute for
Cognitive Science (C-015)
UCSD
La Jolla, CA 92093

Dr. Melissa Holland
Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Keith Holyoak
University of Michigan
Human Performance Center
330 Packard Road
Ann Arbor, MI 48109

Ms. Julia S. Hough
Lawrence Erlbaum Associates
6012 Greene Street
Philadelphia, PA 19144

Dr. James Howard
Dept. of Psychology
Human Performance Laboratory
Catholic University of
America
Washington, DC 20064

Dr. Earl Hunt
Department of Psychology
University of Washington
Seattle, WA 98105

Dr. Ed Hutchins
Intelligent Systems Group
Institute for
Cognitive Science (C-015)
UCSD
La Jolla, CA 92093

Dr. Barbara Hutson
Virginia Tech
Graduate Center
2990 Telestar Ct.
Falls Church, VA 22042

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Dr. Barbel Inhelder
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Dr. Alice Isen
Department of Psychology
University of Maryland
Catonsville, MD 21228

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Department of Psychology
University of South Carolina
Columbia, SC 29208

Dr. Claude Janvier
Directeur, CIRADE
Universite' du Quebec a Montreal
Montreal, Quebec H3C 3P8
CANADA

Dr. Robin Jeffries
Hewlett-Packard Laboratories
P.O. Box 10490
Palo Alto, CA 94303-0971

Dr. Robert Jernigan
Decision Resource Systems
5595 Vantage Point Road
Columbia, MD 21044

Margaret Jerome
c/o Dr. Peter Chandler
83, The Drive
Hove
Sussex
UNITED KINGDOM

Chair, Department of
Psychology
The Johns Hopkins University
Baltimore, MD 21218

Dr. Douglas A. Jones
Thatcher Jones Assoc.
P.O. Box 6640
10 Trafalgar Court
Lawrenceville
NJ 08648

Dr. Marcel Just
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Daniel Kahneman
The University of British Columbia
Department of Psychology
#154-2053 Main Mall
Vancouver, British Columbia
CANADA V6T 1Y7

Dr. Ruth Kanfer
University of Minnesota
Department of Psychology
Elliott Hall
75 E. River Road
Minneapolis, MN 55455

Dr. Mary Grace Kantowski
University of Florida
Mathematics Education
359 Norman Hall
Gainesville, FL 32611

Dr. Milton S. Katz
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Frank Keil
Department of Psychology
Cornell University
Ithaca, NY 14850

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IBM T. J. Watson Research Ctr.
P.O. Box 218
Yorktown Heights, NY 10598

Dr. Dennis Kibler
University of California
Department of Information
and Computer Science
Irvine, CA 92717

Dr. David Kieras
University of Michigan
Technical Communication
College of Engineering
1223 E. Engineering Building
Ann Arbor, MI 48109

Dr. Peter Kincaid
Training Analysis
& Evaluation Group
Department of the Navy
Orlando, FL 32813

Dr. Walter Kintsch
Department of Psychology
University of Colorado
Campus Box 345
Boulder, CO 80302

Dr. David Klahr
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Marie Knerr
Program Manager
Training Research Division
HumRRO
1100 S. Washington
Alexandria, VA 22314

Dr. Janet L. Kolodner
Georgia Institute of Technology
School of Information
& Computer Science
Atlanta, GA 30332

Dr. Stephen Kosslyn
Harvard University
1236 William James Hall
33 Kirkland St.
Cambridge, MA 02138

Dr. Kenneth Kotovsky
Department of Psychology
Community College of
Allegheny County
800 Allegheny Avenue
Pittsburgh, PA 15233

Dr David H. Krantz
2 Washington Square Village
Apt. # 15J
New York, NY 10012

Dr. Benjamin Kuipers
University of Texas at Austin
Department of Computer Sciences
T.S. Painter Hall 3.28
Austin, Texas 78712

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Dr. David R. Lambert
Naval Ocean Systems Center
Code 441T
271 Catalina Boulevard
San Diego, CA 92152-6800

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University of California
Department of Information
and Computer Science
Irvine, CA 92717

Dr. Marcy Lansman
University of North Carolina
The L. L. Thurstone Lab.
Davie Hall 013A
Chapel Hill, NC 27514

Dr. Jill Larkin
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

Dr. Jean Lave
School of Social Sciences
University of California
Irvine, CA 92717

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Information Sciences, FRL
GTE Laboratories, Inc.
40 Sylvan Road
Waltham, MA 02254

Dr. Alan M. Lesgold
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Jim Levin
Dept. of Educational Psy.
210 Education Building
1310 South Sixth St.
Champaign, IL 61810-6990

Dr. John Levine
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Michael Levine
Educational Psychology
210 Education Bldg.
University of Illinois
Champaign, IL 61820

Dr. Clayton Lewis
University of Colorado
Department of Computer Science
Campus Box 430
Boulder, CO 80309

Matt Lewis
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213

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Mail Code SR 111
NASA Johnson Space Center
Houston, TX 77058

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Chief of Naval Education
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Pensacola, FL 32508

Dr. Sandra P. Marshall
Dept. of Psychology
San Diego State University
San Diego, CA 92182

Dr. Manton M. Matthews
Department of Computer Science
University of South Carolina
Columbia, SC 29208

Dr. Richard E. Mayer
Department of Psychology
University of California
Santa Barbara, CA 93106

Dr. Joe McLachlan
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. James McMichael
Assistant for MPT Research,
Development, and Studies
OP 01B7
Washington, DC 20370

Dr. Barbara Means
Human Resources
Research Organization
1100 South Washington
Alexandria, VA 22314

Dr. Douglas L. Medin
Department of Psychology
University of Illinois
603 E. Daniel Street
Champaign, IL 61820

Dr. George A. Miller
Department of Psychology
Green Hall
Princeton University
Princeton, NJ 08540

Dr. William Montague
NPRDC Code 13
San Diego, CA 92152-6800

Dr. Allen Munro
Behavioral Technology
Laboratories - USC
1845 S. Elena Ave., 4th Floor
Redondo Beach, CA 90277

Chair, Department of
Computer Science
U.S. Naval Academy
Annapolis, MD 21402

Dr. Allen Newell
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Richard E. Nisbett
University of Michigan
Institute for Social Research
Room 5261
Ann Arbor, MI 48109

Distribution List [Illinois/Gentner] NR 667-551

Dr. Mary Jo Nissen
University of Minnesota
N218 Elliott Hall
Minneapolis, MN 55455

Director, Training Laboratory,
NPRDC (Code 05)
San Diego, CA 92152-6800

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San Diego, CA 92152-6800

Dr. Harold F. O'Neil, Jr.
School of Education - WPH 801
Department of Educational
Psychology & Technology
University of Southern California
Los Angeles, CA 90089-0031

Dr. Michael Oberlin
Naval Training Systems Center
Code 711
Orlando, FL 32813-7100

Dr. Stellan Ohlsson
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Office of Naval Research,
Code 1133
800 N. Quincy Street
Arlington, VA 22217-5000

Office of Naval Research,
Code 1142
800 N. Quincy St.
Arlington, VA 22217-5000

Psychologist
Office of Naval Research
Branch Office, London
Box 39
FPO New York, NY 09510

Special Assistant for Marine
Corps Matters,
ONR Code 00MC
800 N. Quincy St.
Arlington, VA 22217-5000

Psychologist
Office of Naval Research
Liaison Office, Far East
APO San Francisco, CA 96503

Dr. Judith Orasanu
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Prof. Seymour Papert
20C-109
Massachusetts Institute
of Technology
Cambridge, MA 02139

Dr. James Paulson
Department of Psychology
Portland State University
P.O. Box 751
Portland, OR 97207

Dr. Roy Pea
Bank Street College of
Education
610 W. 112th Street
New York, NY 10025

Dr. Douglas Pearse
DCIEM
Box 2000
Downsview, Ontario
CANADA

Dr. James W. Pellegrino
University of California,
Santa Barbara
Department of Psychology
Santa Barbara, CA 93106

Dr. Virginia E. Pendergrass
Code 711
Naval Training Systems Center
Orlando, FL 32813-7100

Military Assistant for Training and
Personnel Technology,
OUSD (R & E)
Room 3D129, The Pentagon
Washington, DC 20301-3080

Dr. David N. Perkins
Educational Technology Center
337 Gutman Library
Appian Way
Cambridge, MA 02138

Dr. Nancy Perry
Chief of Naval Education
and Training, Code 00A2A
Naval Station Pensacola
Pensacola, FL 32508

Department of Computer Science,
Naval Postgraduate School
Monterey, CA 93940

Dr. Steven Pinker
Department of Psychology
E10-018
M.I.T.
Cambridge, MA 02139

Dr. Tjeerd Plomp
Twente University of Technology
Department of Education
P.O. Box 217
7500 AE ENSCHEDE
THE NETHERLANDS

Dr. Martha Polson
Department of Psychology
Campus Box 346
University of Colorado
Boulder, CO 80309

Distribution List [Illinois/Gentner] NR 667-551

Dr. Peter Polson
University of Colorado
Department of Psychology
Boulder, CO 80309

Dr. Steven E. Poltrock
MCC
9430 Research Blvd.
Echelon Bldg #1
Austin, TX 78759-6509

Dr. Harry E. Pople
University of Pittsburgh
Decision Systems Laboratory
1360 Scaife Hall
Pittsburgh, PA 15261

Dr. Mary C. Potter
Department of Psychology
MIT (E-10-032)
Cambridge, MA 02139

Dr. Joseph Psotka
ATTN: PERI-1C
Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333

Dr. Lynne Reder
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. James A. Reggia
University of Maryland
School of Medicine
Department of Neurology
22 South Greene Street
Baltimore, MD 21201

Dr. Fred Reif
Physics Department
University of California
Berkeley, CA 94720

Dr. Lauren Resnick
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Dr. Gil Ricard
Mail Stop C04-14
Grumman Aerospace Corp.
Bethpage, NY 11714

Mark Richer
1041 Lake Street
San Francisco, CA 94118

Dr. Mary S. Riley
Program in Cognitive Science
Center for Human Information
Processing
University of California
La Jolla, CA 92093

Dr. Linda G. Roberts
Science, Education, and
Transportation Program
Office of Technology Assessment
Congress of the United States
Washington, DC 20510

Dr. William B. Rouse
Search Technology, Inc.
25-b Technology Park/Atlanta
Norcross, GA 30092

Dr. David Rumelhart
Center for Human
Information Processing
Univ. of California
La Jolla, CA 92093

Dr. Roger Schank
Yale University
Computer Science Department
P.O. Box 2158
New Haven, CT 06520

Dr. Walter Schneider
Learning R&D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

Dr. Alan H. Schoenfeld
University of California
Department of Education
Berkeley, CA 94720

Dr. Janet Schofield
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Karen A. Schriver
Department of English
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. Judah L. Schwartz
MIT
20C-120
Cambridge, MA 02139

Dr. Marc Sebrechts
Department of Psychology
Wesleyan University
Middletown, CT 06475

Dr. Judith Segal
OERI
555 New Jersey Ave., NW
Washington, DC 20208

Dr. Sylvia A. S. Shafto
Department of
Computer Science
Towson State University
Towson, MD 21204

Dr. Ben Shneiderman
Dept. of Computer Science
University of Maryland
College Park, MD 20742

Dr. Lee Shulman
Stanford University
1040 Cathcart Way
Stanford, CA 94305

Dr. Robert S. Siegler
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Derek Sleeman
Stanford University
School of Education
Stanford, CA 94305

Distribution List [Illinois/Gentner] NR 667-551

Dr. Edward E. Smith
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Richard E. Snow
Department of Psychology
Stanford University
Stanford, CA 94306

Dr. Elliot Soloway
Yale University
Computer Science Department
P.O. Box 2158
New Haven, CT 06520

Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Kathryn T. Spoehr
Brown University
Department of Psychology
Providence, RI 02912

Dr. Robert Sternberg
Department of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

Dr. Albert Stevens
Bolt Beranek & Newman, Inc.
10 Moulton St.
Cambridge, MA 02238

Dr. Thomas Sticht
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. John Tangney
AFOSR/NL
Bolling AFB, DC 20332

Dr. Kikumi Tatsuoka
CERL
252 Engineering Research
Laboratory
Urbana, IL 61801

Dr. Perry W. Thorndyke
FMC Corporation
Central Engineering Labs
1185 Coleman Avenue, Box 580
Santa Clara, CA 95052

Dr. Douglas Towne
Behavioral Technology Labs
1845 S. Elena Ave.
Redondo Beach, CA 90277

Chair, Department of
Computer Science
Towson State University
Towson, MD 21204

Chair, Department of
Psychology
Towson State University
Towson, MD 21204

Dr. Kurt Van Lehn
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Beth Warren
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Donald Weitzman
MITRE
1820 Dolley Madison Blvd.
MacLean, VA 22102

Dr. Keith T. Wescourt
FMC Corporation
Central Engineering Labs
1185 Coleman Ave., Box 580
Santa Clara, CA 95052

Dr. Douglas Wetzel
Code 12
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Barbara White
Bolt Beranek & Newman, Inc.
10 Moulton Street
Cambridge, MA 02238

Dr. Christopher Wickens
Department of Psychology
University of Illinois
Champaign, IL 61820

Dr. Heather Wild
Naval Air Development Center
Code 6021
Warminster, PA 18974-5000

Dr. Michael Williams
IntelliCorp
1975 El Camino Real West
Mountain View, CA 94040-2216

Dr. Robert A. Wisher
U.S. Army Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Mr. John H. Wolfe
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Wallace Wulfeck, III
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Joe Yasatuke
AFHRL/LRT
Lowry AFB, CO 80230

Dr. Masoud Yazdani
Dept. of Computer Science
University of Exeter
Exeter EX4 4QL
Devon, ENGLAND

Mr. Carl York
System Development Foundation
181 Lytton Avenue
Suite 210
Palo Alto, CA 94301

Dr. Joseph L. Young
Memory & Cognitive
Processes
National Science Foundation
Washington, DC 20550

END

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